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THE PREDICTIVE ROLE OF STOCK MARKET RETURN FOR REAL ACTIVITY IN THAILAND

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ABSTRACT

Stock market return is one of financial variables that contain information to forecast real activity such as industrial production and real GDP growth. However, it is still controversial that stock market return can have a predictive content on real activity. This paper attempts to investigate the ability of stock market return to predict industrial production growth (or real activity) in Thailand, which is an emerging market economy. The standard causality test and the equal forecast evaluation of nested models are employed. For the purpose of forecasting, the data are divided into two periods: the data for the in-sample and the out-of-sample periods. The test of equal forecasting ability is also used. Using monthly data from January 1993 to December 2011, it is found that the model augmented with stock return variable outperforms the benchmark model in the forecast horizon of two months. The results seem to support the notion that stock market return is a predictor of industrial output growth in the short run. Moreover, the standard Granger causality test using the in-sample data also supports this notion. The findings offers a useful insight to investors, financial managers and policymakers on the role of stock market return in forecasting real economic activity. Specifically, a change in stock market return is a signal for revising investment decision by investors and portfolio managers.

Key Words: Stock return, real activity, emerging market, forecasting, causality

JEL Classification: E44, C14, C22

INTRODUCTION

The notion that financial variables contain information to forecast real economic activity is still controversial. These financial variables are stock market returns, short-term interest rates, interest rate spreads, and exchange rates. Previous empirical studies have tried to identify what should be the most appropriate variables. For stock return variable, Fama (1981) examines the sources of

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variations in stock returns, which include shocks to expected cash flows, predictable stock return variation caused by changes in the discount rate over time, and shocks to discount rate in the valuation models of stock prices. He reports that large fractions of annual stock variances can be traced to forecasts of crucial variables, such as real GNP, industrial production and investment. These variables are determinants of firms' cash flows. Similar finding can be found in Kaul (1987) and Barro (1990). Schwart (1990) replicates Fama's finding and points out that even though Fama's finding is robust, measures of industrial production are also important to test the relationship between real stock returns and real activity. Lee (1992) employs a multivariate vector-autoregressive model to investigate causal relations and dynamic interactions among asset returns, real activity, and inflation in the United States during the postwar period. One of his main findings is that stock returns appear to Granger cause real activity and also explain its variation. Gallinger (1994) uses Granger causality tests to examine the relationship between real stock returns and real activity and finds that stock returns Granger cause industrial production for a long-span monthly data. Canova and De Nicolo (1995) examine the relationship between stock returns and real activity in a general equilibrium framework. They find that this relationship becomes stronger when foreign influences are taken into account. Cheung and Ng (1998) find long-run co-movements between stock market index and aggregate real activity in the United States, Canada, Germany, Italy, and Japan. Estrella and Mishkin (1998) examine the performance of financial variables as predictors of U. S. recession by focusing on out-of-sample performance from one to eight quarters ahead. The results show that stock prices can predict real output from one to three quarter horizons. Choi et al. (1999) investigate the relationship between industrial production growth rates and lagged real stock returns in the G-7 countries. They find that correlation between the two variables is significant in all countries, except Italy. Hassapis and Kalyvitis (2002) develop a simple growth model that represents the relationship between real stock prices and output to test the link between real stock return and economic growth. Their results show strong relationships for the G-7 economies. Dumas et al. (2003) find that there exist reasonable correlations between stock returns and outputsin 12 OECD countries. Stock and Watson (2003) also indicate the importance of other variables, i.e. money supply, exchange rates, and oil prices in predicting output growth in the case of the United States. Banerjee et al. (2005) obtain the results that support the widely belief that various variables can act as leading indicators of output growth in the Euro area. Shahbaz et al. (2008) also reported that stock market development promotes economic growth in Pakistan.

Most empirical studies focus on the relationships between financial variables and the macroeconomic activities in the United States and other advanced economies. However, this relationship is less known in small open or emerging market economies. Aylward and Glen (2000) use annual average data from 23 markets, both advanced and emerging stock markets, to test the relationship between stock prices and real output. They find mixed results, i.e. the significant coefficient of lagged stock prices is observed in only 6 out of 23 cases when the least squares method is employed. Similar study by Mauro (2003) uses panel data of emerging and advanced economies to investigate correlation between stock returns and output growth and finds that the proportion of countries with the correlation between output growth and lagged stock returns is significantly positive when annual data are used. However, the proportion is lower when quarterly data are used. In addition, the results are almost the same for advanced and emerging market economies. Employing monthly industrial production indexes of EU countries covering the period from January 1988 to May 2005 to construct out-of-sample forecasts and evaluation, Panopoulo (2007) finds that stock market return is one of financial variables that provide most accurate forecasts for output growth. Tsouma (2009) examines the dynamic interdependence between stock returns and economic activity in emerging and advanced markets using monthly data and discovers the existence of relationship between stock returns and real activity. However, the forecasting ability running from stock returns to economic activity is confirmed for a small number of emerging markets, but for a large number of mature markets. Ibrahim (2010) finds that the predictive role of stock returns for real activity at short horizon is found in case of Malaysia. Kuosmanen and Vataja (2011) investigate the forecasting content of stock returns and volatility, and the term spread for GDP, private consumption, industrial production and the inflation rate in Finland. Their results suggest that during normal times, the term spread is a much better tool than stock market variables for predicting real activity. However, during the financial crisis, the forecast performance is improved by combining the term spread and the stock market information.

The stock exchange of Thailand is one of Asian emerging stock markets. Since its inauguration in April 1975, the market capitalization has expanded mainly due to the 1992 financial liberalization. The Thai government has also implemented some measures to induce capital inflow, specifically portfolio and foreign direct investment. As a consequence, the volume of trading has gradually increased. After the financial liberalization, the market capitalization was 1.485 million baht at the end of 1992 and increased to 3.325 million baht at the end of 1993. The 1997 financial crisis caused the capitalization to decrease substantially. The market capitalization recovered at the end of 2003 with the value of more than 4 million baht, and increased to more than 8 million baht the end of 2010. Industrial production or its growth rate can be considered as real economic activity for some emerging market economies, including Thailand. The long-run effect of capital accumulation on GDP growth by manufacturing firms has been recognized in the economic development literature. De Long and Summers (1991) indicate that countries that reach high level of economic development seem to have higher equipment investment. Industrial production in Thailand has been in a rising trend even though there was a large interruption caused by the 1997 financial crisis. Movements in real activity can be affected by movements in stock market index. The main purpose of this study is to examine the predictive role of stock market return for industrial output growth during January 1993 to December 2011. It is found that stock market return has a predictive content on industrial output growth. The paper is organized as follows. Section 2 explains the estimation methods. Section 3 describes the data and presents empirical results. The last section concludes.

Estimation Methods

The Standard causality test and the models for forecasting are used in investigating the predictive content of stock market return on real activity.

Bivariate Granger Causality Test

Granger causality test proposed by Granger (1969) allows for investigating a bivariate relationship between industrial output growth (*y*) and stock return (*r*). In a bivariate framework, the test is conducted by the following equations:

$$y_t = \alpha_{1,0} + \sum_{i=1}^{k} \beta_{1,i} r_{t-i} + \sum_{i=1}^{k} \gamma_{1,i} y_{t-i} + e_{1,t} \tag{1}$$

$$r_t = \alpha_{2,0} + \sum_{i=1}^{k} \beta_{2,i} y_{t-i} + \sum_{i=1}^{k} \gamma_{2,i} r_{t-i} + e_{2,t} \tag{2}$$

The optimal lag *k* can be determined by Akaike information criterion (AIC). Equation (1) is used to test the hypothesis that current output growth is caused by lagged stock return while equation (2) is used to test the hypothesis that current stock return is caused by lagged output growth. If *r* causes *y* in this standard Granger causality test then *r* can be a predictor for *y* in the short-run forecast ability (Maddala and Kim, 1998). Therefore, if stock return contains a predictive content on output growth, the lagged *r* must influence current *y*. This test is also employed in Lee (1992) and Tsouma (2007).

Autoregressive Distributed Lag Model

Fama (1990) finds that lags of real stock return provide information about industrial production growth in the United States. Stock and Watson (2003) add the growth rate of money supply, exchange rates, and oil prices as predictors of real activity in the United States. Banerjee et al. (2005) emphasize the importance of various variables in forecasting real activity in the Euro area. However, Panopoulo (2007) provides the evidence that stock return is one of several financial variables that add more highly significant predictive content on output growth when the autoregressive distributed lag (ADL) model with single linear equation is used. The ADL model also outperforms non-linear and multivariate models. The equation for ADL model is specified as the following:

$$y_{t+h} = c + \alpha(L) y_t + B(L) Z_t + \varepsilon_{t+h} \tag{3}$$

where *c* is a constant, $\alpha(L)$ is a scalar lag polynomial, *B(L)* is a vector of lag polynomial, and Z_t is a vector of financial variables as predictors. Similar to the standard causality test, AIC can be used in selecting the number of lags for both y_t and Z_t. When *B(L)* is zero, the model in equation (3) becomes the simple autoregressive (AR) model, which can be used as a benchmark when evaluating the forecasts of several models.[2] In a simple form of two variables, the model in equation (3) is specified as the following equation.

$$y_{t+h} = c + \sum_{i=0}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_i r_{t-j} + \varepsilon_{t+h} \tag{4}$$

where y is output growth, and r is stock market return. The optimal lags of output growth and stock return are p and q respectively. When equation (4) is employed, one can include the financial crisis dummy into the equation. The benchmark model is specified as the following equation:

$$y_{t+h} = c + \sum_{i=0}^{p} \alpha_i y_{t-i} + \varepsilon_{t+h} \tag{5}$$

The model in equation (4) is tested against the model in equation (5). Equations (4) and (5) are nested models. The order q in equation (4) is the number of parameters that exceeds the parameters of the benchmark model of equation (5).

In evaluating the forecast performance of the two nested models, one can construct the out-of-sample forecast statistic which is specified as:

$$MSFE = (\sum_{t}^{m-h} \varepsilon_{f,t+h}^2) / m) \tag{6}$$

where *MSFE* is the mean squared forecast error, m is the number of the out-of-sample observations, and f stands for forecast, h is the forecast horizon, and $\varepsilon^2$is the squared forecast error. If the benchmark model outperforms the model augmented with stock return and its lags, its *MSFE* must be lower, and vice versa. McCraken (2007) offers the out-of-sample (OOS) F-statistic which is specified as:

$$OOS - F = [\sum_{t=1}^{m-h} (\varepsilon_{f,1,t+h}^2 - \varepsilon_{f2,t+h}^2) /(m-h)^{-1} \sum_{t=1}^{m-h} \varepsilon_{f2,t+h}^2] \tag{7}$$

where $\varepsilon_{f,1,t+h}^2$ and $\varepsilon_{f,2,t+h}^2$ are the squared forecast errors of the benchmark and the augmented model, respectively.

This computed F-statistic is used to compare with critical F-statistic in case the recursive least square estimate is used. The critical F-statistic is tabulated in Table-4 of McCraken (2007). When the computed *OOS-F* is greater than the critical *F*, the null hypothesis that the nested models are equivalent is rejected. On the contrary, when the computed *OOS-F* is less than the critical value, the null hypothesis cannot be rejected.

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[2]Ibrahim (2010) also uses this model to test for forecasting ability of nominal stock market return on real economic activity in the case of Malaysia.

Data and Empirical Results

The monthly data of stock prices (stock market index) and industrial production index during the 1993-2011period are used.[3] These data are obtained from the Bank of Thailand. The industrial production growth rate is calculated as monthly percentage change in industrial production index. In a similar manner, the stock market return is calculated by monthly percentage change in stock market index throughout the whole sample period[4]. The growth rate of industrial output and stock return are stationary using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results are reported in Table-1.

Table-1. Results from unit root tests

	ADF(intercept)	ADF(intercept and trend)	PP (intercept)	PP(intercept and trend)
A. Whole sample period: January 1993 to December 2011				
Y	-4.011 [9] (0.002)***	-4.093 [12] (0.008)**	-16.780 [10] (0.000)***	-16.730 [11] (0.000)***
R	-13.953 [0] (0.000)***	-13.958 [0] (0.000)***	-13.952 [0] (0.000)***	-13.957 [1] (0.000)***
B. In-sample period: January 1993 to December 2006				
Y	-5.484 [5] (0.000)***	-6.708 [4] (0.000)***	-22.867 [3] (0.000)***	-23.092 [4] (0.000)***
R	-12.348 [0] (0.000)***	-12.327 [0] (0.000)***	-12.338 [5] (0.000)***	-12.316 [5] (0.000)***

Note: The variable *y* is the growth rate of industrial output, and *r* is the stock return. The number in parenthesis is p- value and the number in bracket is optimal lag length determined by Akaike information criterion for ADF tests and determined by the optimal bandwidth determined by the Bartlett kernel for PP tests. ***, and ** denote significant at the 1 and 5 percent levels respectively.

The results from unit root tests show that the two series are stationary because the null hypothesis of unit root is rejected in all four tests for the whole sample and in-sample periods. The results meet the requirement of stationarity property of the two series that are used in the standard Granger causality test and the estimates of the ADL models. The bivariate causality test is performed on in-sample data, the results are reported in Table-2. The results are sensitive to the lag length. The optimal number of lag determined by Akaike information criterion (AIC) is five. The F-statistic for the null hypothesis that output growth (y) does not cause stock return (r) is accepted. The F-statistic for the null hypothesis that stock return (r) does not cause industrial output growth (y) is 3.051 with the p-value of 0.012. Therefore, the null hypothesis is rejected at the 5 percent level of significance[5]. In the estimated equation, the result shows that the coefficient of r_{t-3} in bivariate

[3]Official quarterly real GDP data are available from 1993 to 2010 with 68 observations, but the sample size is too small to perform in-sample estimates and out-of-sample forecasts. Thus monthly data of industrial production index are used instead. In addition, industrial production generates forward and backward linkages and is a good proxy for real economic activity.

[4]The use of nominal stock return is sound in that investors and portfolio managers will usually forecast the market index for their investment decision.

[5]The results from Granger causality test in the present paper are the same as those reported by Tsouma (2009) who uses real stock return and industrial production growth for Thailand during 1991 and 2006.

Granger causality test is 0.065 with the p-value of the t-statistic of 0.003, which is significant at the 1 percent level. In other words, one-month lagged stock return provides the predictive content on two-month forecast of output growth, which is equivalent to stating that three-month lagged stock return provides the predictive content on current output growth. Stock and Watson (2003) state that rejection of in-sample Granger causality tests provide a poor guide for forecast performance because the rejection does not give useful information about the predictive relation. However, the results from the present analysis show that there is unidirectional causality running from stock return to output growth with a positive causation.

Table-2. Results from bivariate Granger causality test: January 1993 to December 2006

Lag length	H_o: *r* does not cause *y*	H_o: *y* does not cause *r*
k=2	0.201[+] (0.818)	0.898 [+] (0.371)
k=4	1.976[+] (0.101)	0.779[+] (0.541)
k=6	3.083***[+] (0.007)	0.654 [+] (0.687)
k=8	2.052**[+] (0.014)	0.455 [+] (0.886)

Note: The number in parenthesis is p-value. ***, and * denotes significance at the 1 and 10 percent level, respectively. The variable *y* is the growth rate of industrial output, and *r* is the stock return. The number in bracket indicates positive causal relationship. [+] denotes positive causal relationship.

For the purpose of forecasting, the data are divided into two periods: the in-sample period starts from January 1993 to December 2006, and the out-of-sample period starts from January 2007 to December 2011. There are 164 and 60 observations for the in-sample and out-of- sample periods, respectively. Equation (4) is estimated for the in-sample period and the results are reported in Table-3[6]. The estimates of Table-3 start from selecting the optimal lags of *p* in the autoregressive order using AIC. The order *p* is equal to six. By adding the variable *r* (stock return) and its lags to the autoregressive model of *y* (industrial output growth), the lag order of *r* is five. The adjusted R^2 is quite low and varies when the forecast horizon (*h*) increases. However, the *F*-statistic shows highly significance up to twenty-four month forecast horizon, except the forecast horizon of eight months.

Table-3. Results from h-month ahead forecasts of industrial production growth: 1993M1-2006M12

Coefficient	Forecast horizon				
	h=2	*h*=4	*h*=8	*h*=16	*h*=24
C	0.319 (0.491)	0.404 (0.386)	0.305 (0.533)	0.145 (0.383)	0.039 (0.480)

[6]The one-month forecast horizon is also employed, but the results do not display any success in forecasting ability. The pattern of forecasting horizons might not be the same with different datasets. Panopoulou (2007) reports the U-shaped pattern when the h-step ahead forecast horizons increase from 3, 6, and 12 months ahead, i.e., the forecasting performance of the competing models deteriorates at the 3 month horizon, but improves at the 6 and 12 month horizons.

λ	0.133 (0.784)	0.213 (0.661)	0.336 (0.511)	0.649 (0.192)	0.266 (0.626)
α_0	-0.205** (0.026)	-0.177* (0.053)	0.150 (0.120)	-0.123 (0.186)	-0.294*** (0.005)
α_1	0.126 (0.220)	-0.099 (0.338)	0.130 (0.231)	-0.011 (0.920)	-0.154 (0.185)
α_2	-0.157 (0.127)	0.140 (0.174)	-0.029 (0.789)	-0.107 (0.307)	0.063 (0.585)
α_3	-0.168* (0.093)	-0.076 (0.444)	-0.018 (0.863)	-0.154 (0.131)	-0.112 (0.318)
α_4	0.178* (0.069)	0.116 (0.236)	-0.048 (0.642)	0.087 (0.384)	0.093 (0.399)
α_5	-0.035 (0.726)	0.091 (0.360)	-0.140 (0.180)	-0.103 (0.309)	0.189* (0.092)
α_6	0.052 (0.507)	0.033 (0.975)	0.018 (0.839)	-0.157* (0.075)	-0.011 (0.911)
β_0	0.008 (0.742)	-0.040 (0.159)	-0.028 (0.270)	-0.050** (0.043)	-0.011 (0.677)
β_1	0.055** (0.022)	0.071*** (0.004)	0.056** (0.027)	0.054** (0.029)	-0.001 (0.976)
β_2	-0.043* (0.073)	0.006 (0.793)	-0.030 (0.237)	0.011 (0.648)	0.020 (0.453)
β_3	0.053** (0.032)	-0.112 (0.635)	0.045* (0.085)	0.027 (0.282)	-0.031 (0.256)
β_4	0.006 (0.799)	-0.032 (0.190)	0.002 (0.946)	-0.025 (0.314)	0.001 (0.985)
β_5	-0.009 (0.732)	0.063** (0.012)	0.002 (0.936)	0.060** (0.019)	0.024 (0.391)
Adj. R^2	0.147	0.136	0.049	0.114	0.094
F-statistic	2.977*** (0.001)	2.794*** (0.001)	1.597* (0.086)	2,456*** (0.004)	2.183** (0.011)

Note: The estimated equation is $y_{t+h} = c + \lambda DUM + \sum_{i=0}^{6} \alpha_i y_{t-i} + \sum_{j=0}^{5} \beta_i r_{t-j} + \varepsilon_{t+h}$. DUM stands for the 1997 financial crisis dummy variable that takes the value of 1 from 1997M7 to 2006M12, and zero otherwise. The variable *y* is the growth rate of industrial output, and *r* is the stock return. The number in parenthesis is p-value, ***, **, and * denote significance at the 1, 5 and 10 percent respectively.

The coefficient of the dummy variable is not significant for each forecast horizon, which implies that the 1997 financial crisis does not impose any impact on the estimated equations of the forecast model. The coefficient of one-period lagged stock returns is positive and highly significant for all forecast horizons, except the horizon of eight months. This coefficient is insignificant for the forecast horizon of twenty four months. The overall results in Table-3 show that lagged stock return adds highly significant predictive content on industrial output growth within sixteen months. For the horizon of twenty four months, the predictive power does not exist. The goodness of fit in in-sample estimates is not necessarily reflecting the ability of the model to accurately forecast the out-of-sample data. To assess the predictive power of stock return in predicting industrial output growth, one needs to obtain the recursive estimations with specified forecast horizons in Table-3 from 60 out-of-sample observations starting from January 2007 to December 2011. The recursive least square estimation is used by adding one observation at a time to get the estimated h-step-ahead forecast error for each month in all forecast horizons[7]. These estimations can provide forecast evaluation statistic which is called the mean squared forecast errors (*MSFE*) as shown in equation (6).

Table-4. Evaluating the forecast performance of the two nested models

Forecast horizon	h=2	h=4	h=8	h=16	h=24
MSFE(1)	46.339	52.783	65.091	76.564	84.488
MSFE(2)	40.198	52.282	65.085	71.998	83.578
Ratio of *MSFE*(1) and *MSFE*(2)	1.153	1.010	1.000	1.063	1.010
OOS F-statistic	8.861	0.537	0.000	2.790	0.392

Note: *MSFE* (1) is the mean square forecast error of the benchmark model, *MSFE*(2) is that of the model with current and lagged stock return variables. *OOS F-statistic* is the out-of-sample F statistic.

The *MSFE* illustrates the potential improvement in forecasting industrial output growth when current and lagged stock return variables are added to the benchmark model. In addition, the out-of-sample (*OOS*) F-statistics are also computed to test whether the *MSFE* of the forecast model with lagged stock return variables is lower than the benchmark model. The results are shown in Table-4. The results show that *MSFE* of the benchmark model is greater than that of the model with lagged stock return variables for the forecast horizons of two months as can be seen by the ratio of *MSFE(1)/MSFE(2)* is greater than one, except the eight-month forecast horizon. However, the critical value of the OOS F-statistic with six excess parameters (r_t and its five lags) of the two nested model is 8.164 at the 5 percent level of significance. The OOS-F statistic is 8.861, which is greater than the critical value. Therefore, the null hypothesis of equivalent predictive contents is rejected for the forecast horizon of two months. The results show the validity of the out-of-sample two-month-ahead forecast. The evidence confirms the existence of lagged effects of stock return on real activity. In other words, the forecast of output growth improves when stock return data are used. Even though there are two lagged stock returns (r_{t-1} and r_{t-3}) that affect output growth at the 5 percent level of significance, the shortest lagged effect is one (i.e. r_{t-1}). This evidence suggests that the lagged effect of stock return on real activity occurs within a short horizon of three months or a quarter. Furthermore, forecasters will not be able to anticipate the path of output growth from its past history alone because considering lagged stock returns in the forecast model can be more advantageous in forecasting future growth rate of output. In short, it can be concluded that there is a short-run predictability of stock return on industrial output growth. It should be noted that the results from the forecast models are consistent with the causality test results in that they provide the same evidence of the predictive content of stock return on output growth.

[7]According to Stock and Watson (2003), out-of-sample predictive content can be conducted by estimating the in-sample data up to the period just before the period that one wants to forecast. All model selection and estimation must be done using data available prior to making forecast. The recursive estimation can be done by adding one observation at a time. As a result, a sequence of out-of-sample forecasts is produced.

CONCLUSION

This paper attempts to investigate the ability of stock market return to predict industrial production growth or real activity in Thailand, which is an emerging market economy. The study applies the standard Granger causality test and the estimations of the nested models for forecasting to the monthly data of stock market return and industrial production growth during the period from January 1993 to December 2011. The use of nominal stock return is sound in that investors and portfolio managers will usually forecast the market index for their investment decision. For the purpose of forecasting, the data are divided into two periods: the in-sample period starts from January 1993 to December 2006, and the out-of-sample period starts from January 2007 to December 2011. There are 164 and 60 observations for the in-sample and out-of- sample periods, respectively. The test of equal forecasting ability for these two nested models is also used.

Even though most previous studies focus on mature markets, this study provides an example of the predictive power of stock return on real activity in an Asian emerging market by evaluating the notion that stock return contains information relating to real economic activity. In other words, the predictive content of stock return on industrial output growth is examined. In the first part of the analysis, the standard Granger causality test using the in-sample data provides the evidence that supports the notion that stock market return is a predictor of industrial output growth during the period of investigation. In the second part, the benchmark model and the model augmented with stock market return variables are compared. The two models are nested. Using the test of equal forecasting ability for these two nested models, it is found that the model augmented with stock return variable outperforms the benchmark model. The results confirm the predictive role of stock market return in a short horizon of three months or a quarter. The evidence can offer a useful insight to investors, portfolio managers and policymakers on the role of stock market in forecasting real economic activity. An increase in stock market return is a signal for an increase in real activity in the next three months. On the contrary, a decline in stock market return will signal a fall in real activity or industrial output growth in the same manner.

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